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Winds, waves, warm waters, weekdays, and which ways boats are counted influence predicted visitor use at an offshore fishing destination

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A R T I C L E I N F O

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A B S T R A C T

Quantifying the number of recreational fishers is important for many aspects of managing coastal resources. Unfortunately, quantifying recreational boaters in offshore settings has proven difficult due to their distance from shore and a lack of cost-effective methods to monitor small boats (<10 m length). We investigated visitor-use at an offshore marine protected area (MPA) in the southeastern USA. We used multiple methods of counting boats (satellites, buoy camera, passive acoustics, and boat-based observations) and a generalized linear modeling approach to identify environmental and calendar-based predictor variables that influenced visitation. Based on the model, predicted visitor-encounter rates were estimated for various weather and calendar-based scenarios, and the probability of detecting a hypothetical change in visitation with each counting method was examined through a power analysis. The most important predictors were day of the week, special day (e.g., tournament), water temperature, and wave height. Boat counts were 2–5 times higher on weekend days than on weekdays. More boats were predicted on weekdays with good weather (defined as water temperature 24 °C, wave height 0.5 m), than weekends with decent weather (17 °C and 1 m). Considering weekends alone, those with good weather were predicted to have 5 times higher visitation than weekends with decent weather. Predicted visitation was highest on calm days, dropped by ~75 % when wave height reached 1 m, and was essentially zero when wave height exceeded 1.5 m. Highest counts were predicted when water temperature was warmest and gradually declined as temperatures cooled. For the buoy camera and passive acoustic boat-count methods, power analysis suggested that 3–6 years of typical samples before and after a hypothetical 25 % increase in visitation would be needed to have an 80 % chance of detecting the change. Other techniques would take 14 or more years of typical samples. The process used here for investigating visitation can be adapted to other offshore or remote locations.

1. Introduction

Coastal managers often seek to quantify the number of recreational boaters visiting offshore destinations. This information is important for managing sustainable fisheries, optimizing regulations for visitors, and minimizing conflicts among users (McCluskey and Lewison, 2008; Parnell et al., 2010; Brownscombe et al., 2019; Shertzer et al., 2019). Unfortunately, counting small boats (<10 m) in offshore settings has proven challenging. Several methods have been implemented, each with their own limitations. Approaches such as shore-mounted camera systems (Keller et al., 2016; Lancaster et al., 2017; Askey et al., 2018; Flynn et al., 2018; Hartill et al., 2020) and boat ramp surveys (Parnell et al., 2010; Hartill et al., 2016; Lynch et al., 2020) that have worked closer to shore are less effective when boaters leave shore from diffuse access points and venture beyond the horizon. Observer boats or aircraft can be dispatched offshore to conduct surveys (Fraidenburg and Bargmann,

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1982; Cabanellas-Reboredo et al., 2014; Askey et al., 2018) but such monitoring can be expensive and infrequent, especially on weekends and holidays when recreational activities primarily take place. New approaches have also been developed including use of satellite imagery provided that resolution is high enough to distinguish small boats, acquisition is frequent enough for adequate monitoring, time of the day that imagery occurs allows useful inference, and clouds do not interfere (Corbane et al., 2008; Bruno et al., 2011). Hydrophones (passive acoustics) that record boat sounds have also been used for assessing visitation (Bruno et al., 2011; Simard et al., 2016). These have the desirable advantage of continuous monitoring but have limited and variable detection range and it can be difficult to interpret individual visitor events and behaviors from sound alone (Kline et al., 2020). Buoy-mounted camera systems are used in some locations, but also have limited range (Kendall et al., 2020). Questionnaires and mobile apps are useful, but depend upon the memory, honesty, and positional awareness of respondents (Venturelli et al., 2017; Bova et al., 2018). Each of these techniques can assess aspects of offshore visitation, but none are able to provide universal coverage at all times, over broad areas, and in all environmental conditions.

Due to the challenges in quantifying boat activity comprehensively in remote locations, predictive modeling has been used to understand patterns of visitor-use, the variables associated with those patterns, and to identify which methods of counting boats are most informative (van Poorten et al., 2015; Lancaster et al., 2017; Askey et al., 2018). Two primary data types are needed to create models of visitation: sample data (i.e., boat counts) and predictor data. Boat-count data can come from the sources mentioned above, and it is often recommended that multiple approaches be used and compared since no single dataset can typically provide unbiased estimates of visitor use (McCluskey and Lewison, 2008; Hartill et al., 2016; Lynch et al., 2020). Predictor data encompass a diversity of variables that can directly or indirectly affect the choice to go fishing. This may include weather conditions (Fraidenberg and Bargmann, 1982; Parnell et al., 2010; Cabanellas-Reboredo et al., 2014; Lynch et al., 2020), day of the week (Sunger et al., 2012; van Poorten et al., 2015; Askey et al., 2018), month/season (Bird et al., 2001; Keller et al., 2016; Askey et al., 2018), and special dates such as holidays, fishery seasons, or tournaments (Bird et al., 2001; Parnell et al., 2010; Flynn et al., 2018; Lynch et al., 2020). By understanding the relationship between the observed boat-count data and these variables, patterns of visitation can be predicted for times lacking boat observations based on their predictor values.

In this study we investigated visitor-use at Gray's Reef National Marine Sanctuary (GRNMS), an offshore marine protected area (MPA) in the southeastern USA. The factors contributing to the challenge of counting visitors to GRNMS are common to many offshore areas and principally include its long distance from shore and the small boats typically used for accessing it. We used generalized linear models to address four main questions. First, what environmental (e.g., wind speed, seasonal water temperature) and calendar-based variables (e.g., weekend, holiday) are important for predicting boat counts at Gray's Reef? Second, what are the relationships between boat counts and those variables? Third, what are predicted visitor-encounter rates under various environmental and calendar-based scenarios that could be used to inform coastal managers and improve the efficiency of their monitoring plans? Last, which of four different methods of counting boats (i.e., satellites, buoy camera, passive acoustics, or boat-based observations) are most precise and powerful for detecting changes in visitor use?

2. Methods

2.1. Study site

The continental shelf in the Atlantic Ocean off the coast of Georgia, USA is primarily covered with sand that gradually slopes deeper to the shelf edge 120 km offshore. The seabed on this broad shelf is punctuated by a number of rocky outcrops and artificial reefs that attract a diversity of fish species that are commonly targeted by recreational anglers in small boats (Riggs et al., 1996; Shertzer et al., 2019). These include not only bottom dwelling species such as black sea bass (*Centropristis striata*), red snapper (*Lutjanus campechanus*), and grouper species (e.g., Gag-*Mycteroperca microlepis*), but also pelagic fishes such as king mackerel (*Scomberomorus cavalla*) (Bird et al., 2001; Kendall et al., 2008, 2009; Williams et al., 2019). Gray's Reef is one of these naturally occurring rocky habitats (NOAA, 1980; Kendall et al., 2005). Located 30 km offshore at a depth of ~20 m, the 57 km^2 area consists of a cluster of limestone ledges and overhangs that have attracted recreational anglers for decades (Fig. 1).

Visitors to GRNMS depart shore from marinas, boat ramps, and private docks in the many rivers and inlets along the Georgia coast. Although the dominant user group is known to be recreational anglers, the number of boats and temporal aspects of visitation such as relative intensity of fishing activities among seasons and days of the week (e.g., weekend versus weekdays, holidays) as well as different environmental conditions (e.g., waves, precipitation) remain poorly understood (NOAA, 2014; Kendall et al., 2020). This lack of count data about visitors to the sanctuary has persisted since the sanctuary was designated nearly four decades ago.

Four approaches have been used to count boats at GRNMS in recent years (Kendall et al., 2020). On- water observations of visiting boats are conducted by sanctuary staff from small research vessels (GRNMS R/V) during their general field operations at the sanctuary and also from small patrol boats by Georgia Department of Natural Resources (GA DNR). Boat counts have also been conducted from available high-resolution (<1 m) satellite imagery collected around mid-day, every 4–5 days. A radial camera mounted to the data buoy has also been used which collects images every two hours from 7:00 AM to 6:20 PM (local time). Lastly, daily numbers of visiting boats have been inferred based on continuous monitoring of underwater sounds by a hydrophone deployed on the seafloor at GRNMS. None of these methods represents complete daily counts of unique boats throughout the sanctuary for the entire year, and each method differed with respect to temporal and spatial coverage. For example, suitable satellites (i.e., WorldView 1–3) provide a single instantaneous snapshot every 4–5 days (revisit interval) of the entire sanctuary, the buoy camera photographs boats every two hours but only within sight of the data buoy (~2 km), and the hydrophone records boats continuously but they must pass within its detection range. Despite these differences, each technique can provide an estimate of the number of visiting boats on a daily timescale. Details on the differing methodologies, strengths, and weaknesses of each dataset are discussed by Kendall et al. (2020). In this study, we use all visitation records for small recreational boats from each of these methods for 2019 to create a predictive model.

2.2. Statistical framework

To evaluate the relationship between the number of boats observed at the sanctuary, weather conditions, and calendar-based predictors, we used generalized linear models (GLMs) with a negative binomial distribution. This statistical framework and distribution is appropriate for count data where the variance in the data is greater than the mean, as is the case here. Boat observations were summarized within each count method as the total number of boats observed on each day, which was used as the response variable. To account for potential differences in boat counts among datasets due to their various methodologies, a categorical predictor for count method was included in the model.

An initial list of 27 potential predictors was compiled by consulting with sanctuary staff, local fisheries enforcement officers, and anglers (Appendix A). Predictor variables included environmental factors such as measured and forecasted wind speed and wave height, as well as calendar-based variables such as day of the week (e.g., Saturday) and special dates (e.g., fishing tournaments). Meteorological and

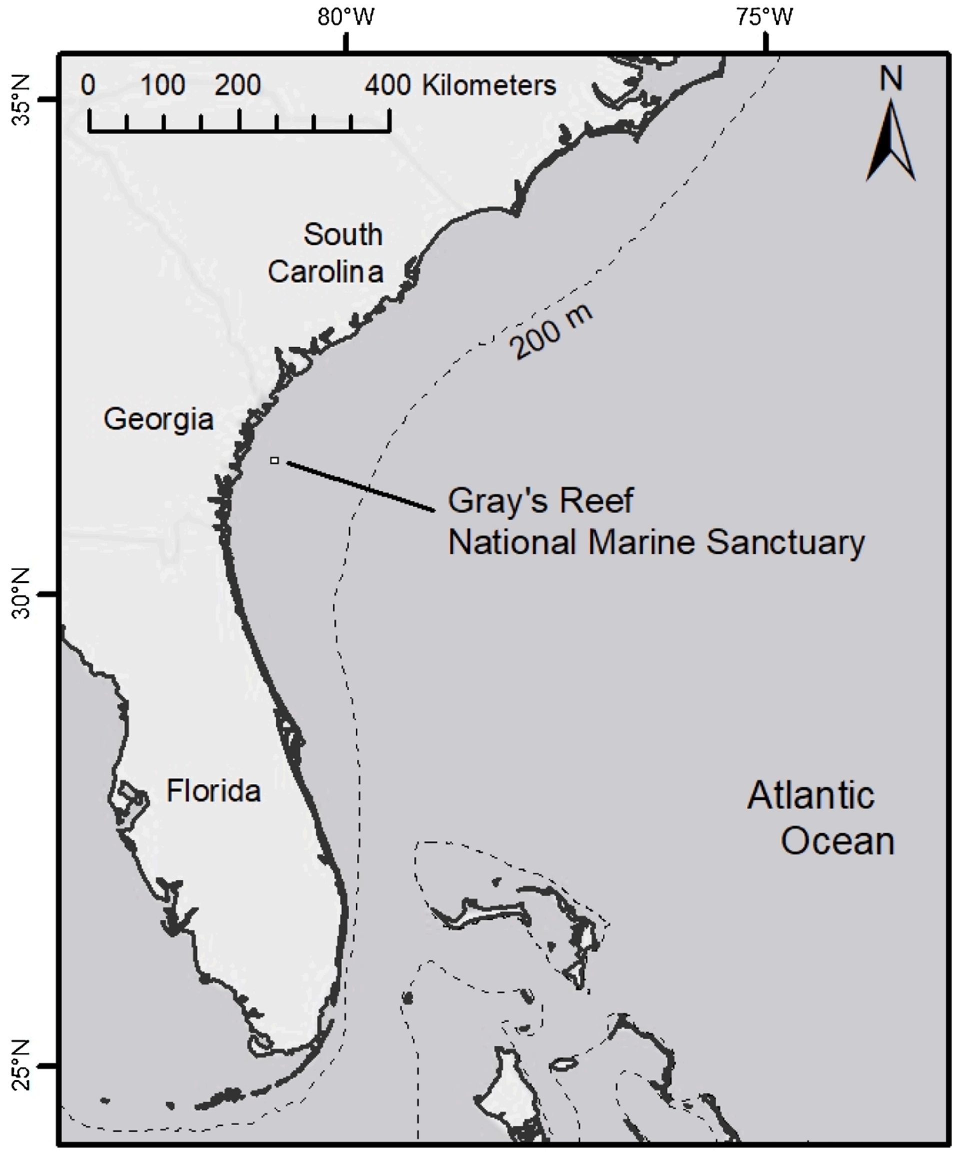

Fig. 1. Study area location off the southeastern USA. The shelf edge is approximately at the 200 m isobath.

oceanographic conditions are measured hourly from the National Data Buoy Center's (NDBC) 3 m disc buoy which is located within GRNMS (Station 41008, https://www.ndbc.noaa.gov/ accessed Jan 15, 2020). Measurements of potentially influential variables on visitor use including wind speed, wave height, water temperature, and direction of atmospheric pressure change were downloaded from the NDBC archive for every day in 2019. Data were evaluated from 6:00 and 11:00 AM local time (GMT -5). Six AM represents conditions at the time boaters may be considering going offshore and 11:00 AM corresponds to the peak time of day for most visitation (Kendall et al., 2020).

Weather forecast data may also influence visitation and could correlate better than observed weather at the time that boats are counted. Boaters often check the forecast for offshore waters when planning a fishing excursion to ensure their comfort and safety and even to improve their chances for successful catch. Weather predictions from the NOAA National Weather Service's Coastal Waters Forecast for GRNMS were downloaded from archive (https://mesonet.agron.iastate.edu/archive/ accessed Jan 15, 2020) for both the evening before and morning of the boat count observations since both times may influence angler decisions. Forecast variables included maximum wind speed, maximum wave height, chance of rain/showers, chance of thunderstorms, and presence/absence of small craft advisories (a type of warning to boaters issued by the US National Weather Service when wind speed exceeds 40 km/h).

Temporal variables, or more precisely, calendar-based variables were also included. These were days of the week (e.g., Monday, Saturday), weekday holidays plus their surrounding weekends (e.g., Labor Day Weekend), dates when fishing tournaments occurred in the vicinity of Gray's Reef that have been historically associated with increased visitation, and dates of fishing seasons (i.e., red snapper) (Table 1). If a holiday fell in the middle of the week (i.e., Tuesday, Wednesday, Thursday), the following (or previous) weekend was not considered a holiday weekend. Dates with holidays, fishing tournaments, and fishing seasons were collectively categorized as "special" because of expected increased visitor use associated with those events.

2.3. *Important predictor variables*

The large list of 27 potential predictors was reduced prior to modeling. Some potential predictors were eliminated due to lack of variation in their values which rendered them unusable for predicting visitation. For example, precipitation forecast was eliminated because the value of this variable was nearly always 'none predicted'. Similarly, atmospheric pressure change (i.e., rising or falling) was excluded due to

Table 1
Dates defined as special days for 2019.

Date	Reason
1/1	New Year's Day
1/19, 1/20, 1/21	Martin Luther King Weekend
2/16, 2/17, 2/18	Washington's Birthday Weekend
5/25, 5/26, 5/27	Memorial Day Weekend
6/14, 6/15	Two Way Sportfishing Club Kingfish Tournament
7/4	Fourth of July
7/12, 7/13	Sapelo Open Kingfish Tournament and red snapper season
7/14	Last day of red snapper season
8/15, 8/16, 8/17	Golden Isles King Mac Attack
8/31, 9/1, 9/2	Labor Day Weekend
10/12, 10/13, 10/14	Columbus Day Weekend
11/9, 11/10, 11/11	Veteran's Day Weekend
11/28	Thanksgiving
12/25	Christmas

a highly consistent pattern of diel change that resulted in almost always rising pressure.

Next, pairs of correlated variables were identified, and only one variable was kept from each pair. The inclusion of correlated predictors in a single model complicates inference about which of those predictors is important given their similar relationship with the response variable. A correlation coefficient >0.7 between predictors has been demonstrated to substantially degrade model inference (Dormann et al., 2013). We chose a somewhat more conservative threshold (Pearson's $r > 0.6$) for excluding pairs of correlated predictors in models (Booth et al., 1994). This aspect of variable reduction was done in two phases; prior to model fitting and during model selection. First we evaluated pairs of variables that differed only in the time that they were collected. For example, all aspects of weather forecasts made the evening before and the morning of a boat count were compared and found to be nearly identical. Although both forecasts are likely consulted when planning a fishing excursion, only the morning forecasts were considered during model fitting because that is the final forecast available before venturing offshore. Similarly, measured weather conditions (e.g., wave height, wind speed, temperature) at 6:00 AM were very similar to their 11:00 AM counterparts. For this analysis, only the 11:00 AM measurements were included during model fitting because they reflect the actual conditions at the sanctuary during visitor use. This process reduced the list of candidate predictor variables from 27 to 12. A few pairs of these remaining predictor variables were correlated ($r > 0.6$) but characterized different aspects of the environment (e.g., wind speed and wave height). We therefore used a model selection process to identify which of each pair best fit the data and which should be eliminated.

To determine the most important predictors explaining the number of boats at GRNMS, a model including all remaining potential predictors was fit using the *glm.nb()* function in the MASS package (Venables and Ripley., 2002) in R Version 3.6.1 (R Core Team, 2019). All potential combinations of predictors were considered for the model using the *dredge()* function in the MuMIn package (Barton, 2020). Models including both of a pair of highly correlated predictors were ignored. The most parsimonious model without highly correlated predictors that best explained the number of boats was identified using the corrected Akaike Information Criterion (AICc). AICc was used instead of cross-validation because cross-validation was impractical with the small sample sizes for some datasets. AICc is a score for evaluating relative performance among multiple models that works by evaluating each model's fit to the available data but adding a penalty for including too many predictors and overfitting the model. Overfitting results in a model that is only relevant to the data used to make it and does not perform well for making general predictions. The model with the lowest AICc score is the best at explaining the number of boats. Models with an AICc score within 2 of the lowest AICc score are similar in performance to the best model. When the AICc score is different by more than 2, models are considerably worse (Burnham and Anderson, 2002). For simplicity, only the best model (that with the lowest AICc score) was used for prediction. The predictors present in the best model were defined as the most important in explaining the number of boats. To measure how well models explained the number of boats, we used percent deviance explained (PDE) which expresses the percentage of variation in the observed boat counts that is explained by the model and is analogous to an R^2 value in a regression.

The relationship between important variables and the predicted number of boats in the best model were plotted (+/- 95 % CI) across the observed range of values for each predictor. To examine the effect of individual variables apart from the effect of the other predictors, all other numeric variables were held at their mean and categorical variables were set to their mode.

2.4. Predicted boat counts

The probability of different numbers of boats being detected at GRNMS across eight weather- and calendar-based scenarios were calculated based on the various counting techniques. This was done to inform the resource managers and organizations conducting the counts about predicted encounter rates such that they may improve the efficiency of their monitoring plans. These scenarios were focused on dates and conditions that were likely to experience relatively high versus moderate visitor use (Fig. 2). Predictions were not created for scenarios unlikely to have many visitors (e.g., bad weather, Mondays). In order to make predictions, specific values for each predictor variable are required. Relevant parameters and their values for these scenarios were determined through discussion with local experts, observations in the field (Kendall et al., 2020), and by examining the observed values of the important predictors identified from the model fitting process.

We began building scenarios based on the day of the week. One set of scenarios was created to represent popular days of the week for visitation (i.e., Friday, Saturday, and Sunday) using Saturday for prediction, and another set of scenarios was created to represent less popular days (i.e., Wednesday or Thursday) using Thursday for prediction. We next added to these scenarios whether or not those days had 'good' (more visitors likely) or 'decent' (fewer visitors likely) weather conditions. The thresholds for 'good' and 'decent' weather were selected by identifying natural break points in scatter plots of observed numbers of boats across

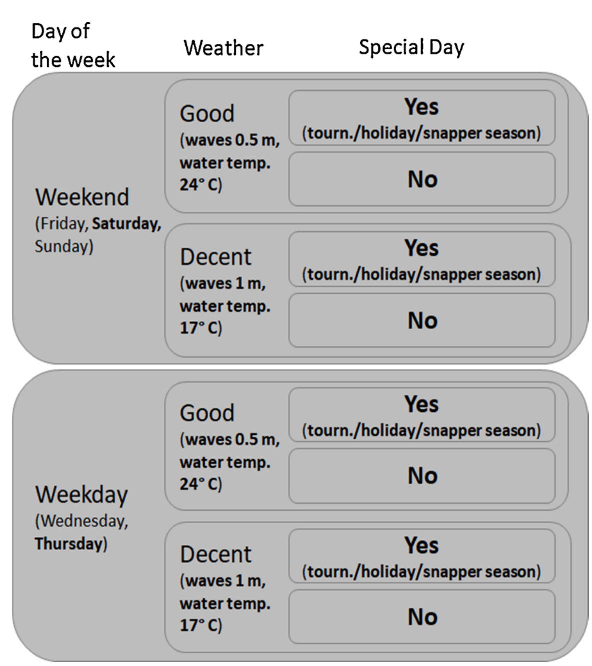

Fig. 2. Variable settings used in the eight boat-count prediction scenarios. Bold values denote the variable levels used to make predictions.

water temperature and wave height, which were identified as important weather variables in the model fitting step. Good weather days were defined as days with many boats observed and where water temperature was above 24 °C and wave height was below 0.5 m, therefore those values were used for predictions representing good weather conditions. Decent weather days with a moderate number of boats observed were defined as having a water temperature of 17−24 °C and wave height of 0.5−1 m. Therefore, those variables were set at the threshold values of 17 °C and 1 m, respectively, for predictions representing decent weather conditions. Lastly, we added to the scenarios whether or not it was a special day. This variable was binary and distinguished predictions occurring on tournament, holiday, and fishing season dates versus all other days. We considered all combinations on good and decent days of day of the week, weather conditions, and special day resulting in eight prediction scenarios (Fig. 2).

The predicted number of boats that would be counted by each technique in a given scenario was simulated from the best model in two steps. First, the mean number of boats was simulated from a normal distribution with mean equal to the corresponding model predicted value and standard deviation equal to the corresponding standard error of the model prediction. These simulated numbers of boats reflected model uncertainty about the predicted mean number of boats, but they did not capture variation in actual boat count data. To account for variation in boat count data, a second simulation step was conducted where for each mean boat count from step 1, an actual boat count was generated from a negative binomial distribution with mean equal to the simulated mean boat count and dispersion equal to that estimated for the model. Simulations were repeated 100,000 times resulting in a distribution of possible boat counts based on each technique within each scenario. The probabilities of observing different numbers of boats were then derived from these distributions.

In addition to predicting boats across these eight hypothetical scenarios, we estimated the total number of boats counted at GRNMS in a given year. Using the conditions of 2019 as an example year, we predicted the number of boats counted at GRNMS each day, given the weather conditions from actual data buoy measurements and weather forecasts, and summed these values through the year.

2.5. Important boat count datasets

We assessed the utility of each boat-count method for understanding visitation in three ways: 1) the ability to identify predictor variables that influenced visitation; 2) the precision of estimated mean counts; and 3) the statistical power to detect changes in visitation. These measures of usefulness are a function of sample size, mean number of boats counted, and the variation in boat counts for each boat-count method.

To assess the ability of each boat-count method to identify predictor variables that influenced visitation we fit a model to each individual dataset (e.g., only passive acoustic data). We then compared the predictors identified as important in the best models (lowest AICc). Then, as a benchmark for comparison, we used the list of important predictors from the best overall model (i.e., from the previous section that was fit using all count methods simultaneously). The GRNMS R/V and GA DNR datasets were combined for this analysis because of their low number of samples, weekend (GA DNR) versus weekday (GRNMS R/V) sampling biases, and general similarity in method.

To assess the precision of estimated mean counts for each boat-count method, we calculated the coefficients of variation (CV; standard error divided by the mean) of the estimated counts for each method. We then compared these values among datasets and to the CV from the best overall model that was fit to all datasets simultaneously.

To assess the statistical power of each boat-count method to detect changes in visitation, we considered a realistic hypothetical situation in which visitation increased by 25 % due to some factor(s) other than the predictor variables considered in our analysis (e.g., coastal population growth). Statistical power essentially represents the probability of correctly detecting that visitation had increased. A power analysis was conducted using custom code in R Version 3.6.1 (R Core Team, 2019) for each boat-count method separately.

The first step in the power analysis was to simulate samples of daily counts for different numbers of years before and after the hypothetical 25 % increase in visitation. Simulated daily counts each year were based on the observed dates and number of samples for each boat-count method. Buoy camera and passive acoustic methods were assumed to sample every day (365 samples per year), a frequency that is possible when the equipment is deployed and maintained. The satellite method was assumed to sample every four days, consistent with the revisit frequency of the satellites used here, beginning on a randomly chosen start date between January 1 and 4 (91 or 92 samples per year). Consistent with 2019, GA DNR was assumed to generate 18 counts per year on weekends (Friday-Sunday) and GRNMS R/V was assumed to generate 6 counts per year on weekdays (Monday-Friday) with good or decent weather conditions (water temperature ≥17 °C and wave height ≤1 m). Simulated sampling dates for the on-water boat-count methods were selected randomly subject to their day-of-week and weather constraints. For each date, the mean count for a given method was calculated using the best overall model assuming the same conditions of that date in 2019. Mean counts from years after the hypothetical increase in visitation were increased by 25 %. Daily counts were randomly generated from a negative binomial distribution with the specified mean and dispersion equal to that of the best overall model.

The second step in the power analysis was to test for a difference in mean visitation between the simulated daily counts before and after the 25 % increase in visitation with a given number of years of samples. A simple negative binomial GLM was fit to each simulated set of data to determine if the estimated mean count after the increase was significantly higher. Power was calculated as the proportion of 10,000 simulated datasets for which an increase was estimated and its p-value was significant (alpha of 0.05).

3. Results

The modeling process included 593 observation days from 2019 (Fig. 3). The passive acoustics dataset from the hydrophone provided the most observations (353) and covered almost the entire year. The camera mounted on the data buoy collected 187 sample days between June (camera deployed) and December (battery expiration). Satellite imagery was collected on 29 days between April and October. Data from 18 GA DNR patrols between January and November, and 6 on-water counts by GRNMS R/Vs collected from June to November, were included.

3.1. Important predictor variables

The best model with the lowest AICc score (AICc = 1001.1, PDE = 43.4) included the predictors boat-count method, day of the week, special day, water temperature, and measured wave height. Only one other model had an AICc score within 2 of the best model and therefore similarly explained boat counts (AICc = 1002.2, PDE = 43.3), and it included the same predictors as the best model, except it included air temperature instead of water temperature. For simplicity, all predictions were made using the model with the lowest AICc score.

Count method was considered an important predictor, indicating that differing methodologies had an effect on the number of boats observed. Specifically, the number of boats counted by the buoy camera was much lower compared to the other datasets, while the number of boats counted from the GRNMS R/V was higher than other methods (Fig. 4a). Two calendar based predictors, day of the week and special day, were also important in explaining boats counted. The most boats were predicted on Saturdays, followed by Sundays and Fridays (Fig. 4b). Additionally, more boats were predicted on days considered special, such as holidays, tournament days, or during the red snapper season (Fig. 4c). Weather conditions including measured water temperature

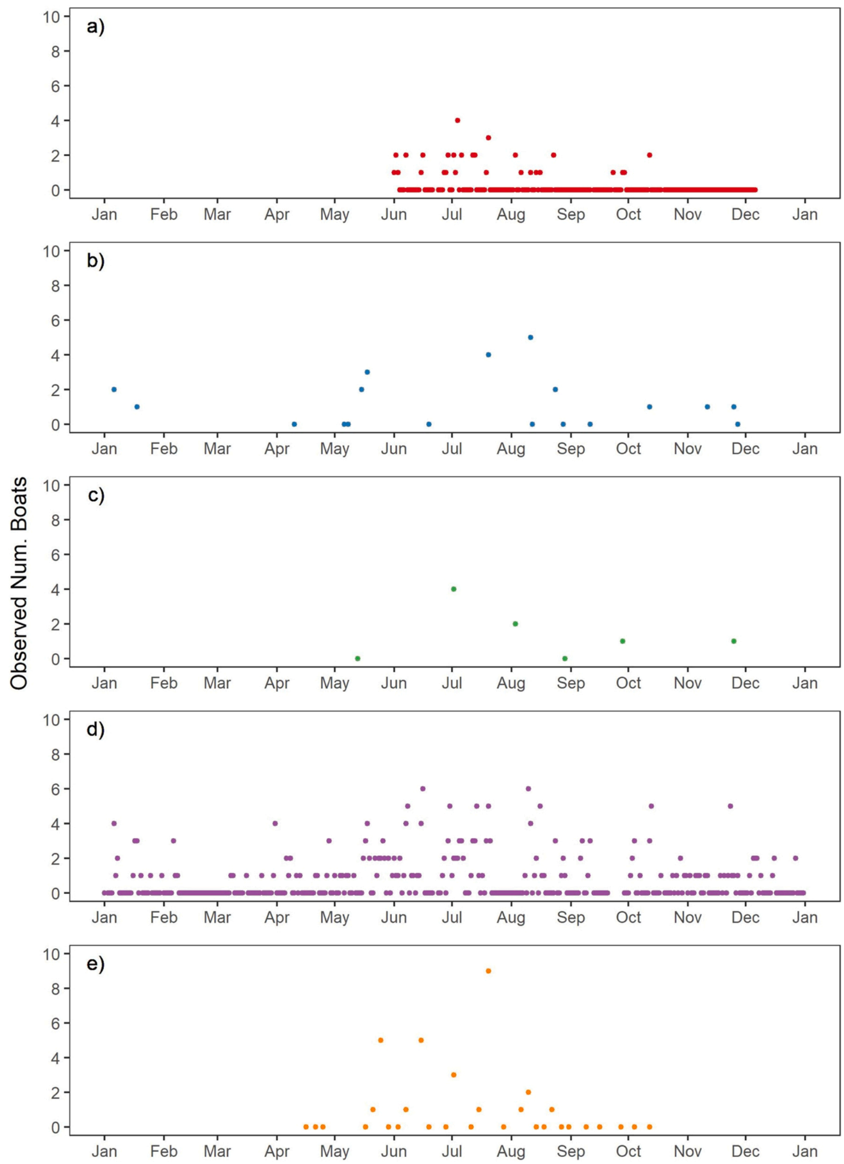

Fig. 3. Number of boats counted at Gray's Reef on a daily basis throughout 2019 based on (a) buoy camera, n = 187 observation days, (b) GA DNR patrols, n = 18, (c) GRNMS R/V observations, n = 6, (d) passive acoustics, n = 353, and (e) satellite images, n = 29.

and wave height, were also important predictors. As water temperature increased, the predicted number of boats counted increased (Fig. 4d). As wave height increased, the number of boats decreased (Fig. 4e).

3.2. Predicted boat counts

The mean number of boats expected to be counted using each method varied based on the different scenarios of good or decent weather, weekend or weekday, and special day status (Fig. 5). The highest mean boat counts were predicted on weekend/good weather/special days. These were 27 times higher than predicted on weekdays with decent weather (Fig. 5). Considering weekends alone, the most popular days of visitation, those with good weather were predicted to have 5 times higher mean boat counts than weekends with only decent weather. Also of note, more boats were predicted on weekdays with good weather, than weekends with decent weather.

It is important to recognize that these predictions are mean boat counts. The variability in actual counts on any particular visit is likely to be large, even on days with similar attributes. This is best appreciated by examining the histograms displaying the probability of occurrence of different numbers of boats for each count method and scenario (Fig. 6).

The probability distributions of encountering boats sum to 1 (100 %) for each count method within each scenario (Fig. 6). Higher counts, above 8–11 boats per day, are seldom likely on anything other than a weekend with good weather in any technique (Fig. 6 a–b). The histograms also highlight the variability in possible boat counts within each scenario and count method. Even on special weekend days with good weather, it is possible to encounter zero boats, although it is more likely that 1–7 boats will be observed depending on the method (Fig. 6a). Once weather conditions deteriorate from good to decent, all techniques are most likely to encounter zero boats on any day of the week (Fig. 6f-h) unless perhaps, it is a holiday weekend or tournament (Fig. 6e).

Estimates of the total number of boats that would be observed by each count method based on the daily environmental conditions in 2019 varied widely depending on technique. Buoy camera was lowest (n = 64), followed by satellites (n = 174), GA DNR and passive acoustics (n = 266), and the GRNMS R/V was highest (n = 374).

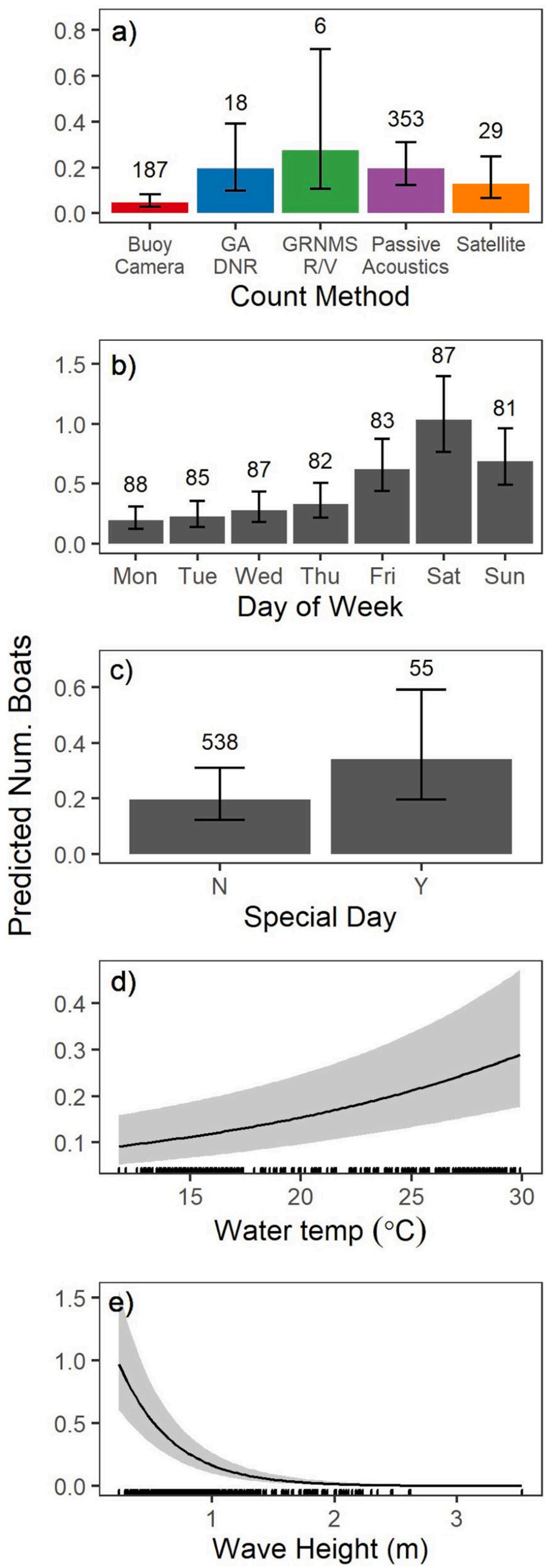

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Fig. 4. a-e. Predicted mean number of boats (+/- 95 % CI) based on the best model by (a) different count methods, b) day of the week, c) special day, d) water temperature, and e) wave height. All variables other than the one on the x-axis were held at their mean for numeric (water temperature =23.8 °C, wave height =0.93 m) or mode for categorical predictors (day of the week = Monday, special day = No). Values above bars on (a-c) represent the number of observations in each category and tick marks on the x axis of (d) and (e) represent observed x values. Only predicted boat counts based on the passive acoustics dataset are displayed in (b-e) as an example, although all count-methods had similar patterns.

3.3. Important boat count datasets

Boat count methods that provided larger samples, or more observation days, were better able to identify predictor variables that influenced visitation. In models fit using single datasets (e.g., buoy camera only), the predictors that constituted the best model varied across datasets (Table 2). The best model fit to the passive acoustic data, which had the largest sample size, identified similar predictors as the best overall model fit to all datasets, with day of the week, special day, measured water temperature, and wave height as important predictors, but selected forecasted maximum seas instead of wave height. The best model fit to the buoy camera data, the second largest sample size, also included day of the week, special day, and measured water temperature but was the only model to include forecasted wind speed and forecasted showers as important predictors. The best model fit to the satellite data and the best model fit to the GRNMS R/V and GA DNR patrol data, the lowest sample sizes, each identified only two important predictors: day of the week and wave height, and forecasted maximum seas and air temperature, respectively. The estimated relationships between important predictors and the number of boats counted at the sanctuary were consistent regardless of the dataset modeled. For example, the relationship to counts was always positive with temperature and was always negative with wave height. Counts were always estimated to be highest on special days and Saturdays.

Boat-count methods that provided larger samples also had more precise estimates of mean counts. In the best overall model, the coefficients of variation of estimated mean counts by boat-count method in increasing order were passive acoustics, buoy camera, satellite, GA DNR, and GRNMS R/V (CV range was 0.15−0.45; Table 2) reflecting a decrease in precision with decreasing sample size. Also of note, PDE values for models based on single datasets varied from just 23 % for the model based on GA DNR-GRNMS R/V counts to 80 % for the model based only on satellite data.

The power analysis indicated that count methods that provided larger samples provided more statistical power to detect an increase in visitation (Fig. 7). Also, for a given sample size, count methods with higher mean daily counts provided more statistical power. For example, both the buoy camera and passive acoustics were assumed to provide 365 daily counts per year, but the buoy camera had lower mean counts (Fig. 4a) resulting in lower power for the same sample size (Fig. 7). For most boat count methods the power analysis suggested that 3–14 years of data before and after a 25 % increase in visitation would be needed to have a statistical power > 0.8 to detect the change (Fig. 7). A statistical power of 0.8 means there is an 80 % chance that one would correctly conclude there had been an increase in visitation when visitation had in fact increased by 25 %. Many more years of GRNMS R/V and GADNR data would be necessary to achieve the same power given the low number of daily counts per year.

4. Discussion

Quantifying recreational anglers in offshore or remote locations is a challenge due to their distance from shore and the costs associated with monitoring them. We address this information gap by using five independent boat count methods to develop a predictive model of visitor use

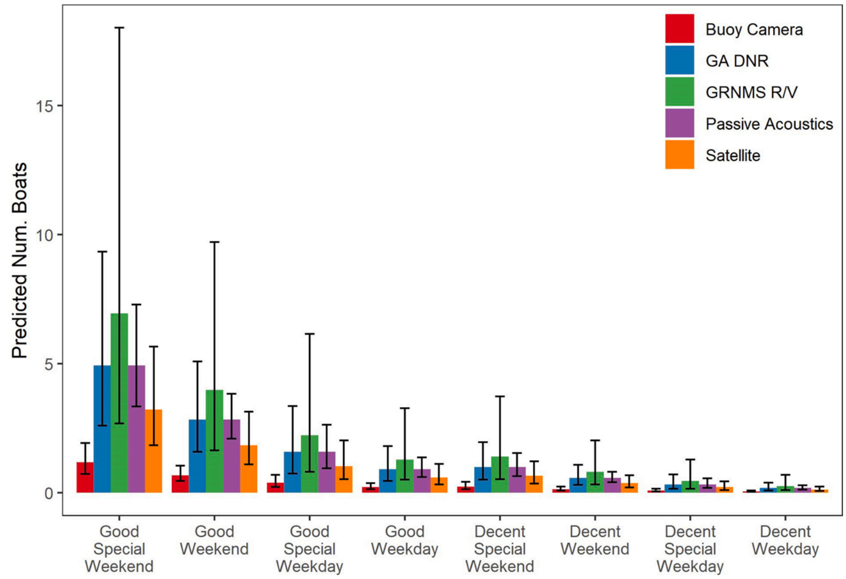

Fig. 5. Predicted mean number of boats (+/- 95 % confidence interval) across weather/calendar scenarios.

at a fishing destination 30 km off the coast of Georgia, USA. We identified a suite of environmental- and calendar based- variables that can predict boat counts on any day of the year. We provide guidance to practitioners of these methods on expected boat counts in different weather conditions and dates, and convey how many years of data would be needed to detect a hypothetical change in visitation.

4.1. Important predictor variables

There were four important environmental and calendar-based predictors of boat counts. These were wave height, water temperature, day of the week, and special day status. Wave height was an important variable related to the physical conditions at the site. The predicted number of boats counted was highest on calm days, dropped by ~75 % when wave height reached 1 m, and essentially no boats were predicted when wave height was 1.5 m or greater assuming average values for all other predictors. These values nearly match the predictions for a recreational squid fishery in the Mediterranean (Cabanellas-Reboredo et al., 2014) which consists of boats similar in size to those used at GRNMS (6−8 m length) (Morales-Nin et al., 2005; Kendall et al., 2020). Large wave heights are not only of concern for the comfort and safety of those in small boats, but they can also make it challenging for anglers to locate and target some bottom features in places like GRNMS. The small ledges and rock features where recreational species congregate can be under 1 m in relief (Kendall et al., 2005, 2008, 2009), meaning that if wave heights exceed the height of such features, locating them with depth sounders can be challenging. Wave height was also simply a better predictor in these models than other variables correlated with it, such as wind speed and small craft advisories.

Water temperature was inversely related to the predicted boat counts at GRNMS. Highest counts were predicted when temperature was warmest (29.9 °C) and then gradually declined as temperatures cooled. Even during the coldest observed value of 11.8 °C, at least some boats were predicted although values were extremely low. It is unclear if this pattern is due to angler comfort, decreased fishing success in colder seasons as migrating fish depart (Parnell et al., 2010; Williams et al., 2019) or some combination of these and other factors. Season is often used as a categorical variable (e.g., summer) during survey design and/or analysis in studies of recreational fishing (Parnell et al., 2010; Keller et al., 2016; Askey et al., 2018), however in this study we used the continuous variable of temperature not only as a proxy for season but in a way that encompasses the more gradual environmental change that actually occurs.

Apart from these environmental predictors, calendar-based variables were also important. Tournaments, holidays, and the brief red snapper fishing season, grouped collectively as special dates in our analysis, are all draws for offshore anglers in the area. Predicted number of boats counted was nearly twice as high on such days compared to others. Many studies on visitor numbers recognize the need to account for events such as holidays that occur on weekdays, and lump those dates in with weekends (Cabanellas-Reboredo et al., 2014; Keller et al., 2016; Flynn et al., 2018; Lynch et al., 2020), whereas others either analyze holidays or long weekends as separate strata (Askey et al., 2018; Lynch et al., 2020), or discuss specific tournaments and dates during interpretation of their results (Flynn et al., 2018). Our results, wherein regular weekend days were predicted to have 40 % less visitation than special weekend days with similar weather, suggest that such events merit analysis in their own separate category in some fisheries.

Day of the week was also an important predictor. Saturday was predicted to have the highest boat counts which clearly fits with visitors comprised primarily of recreational fishers occupied on business days. Sunday and Friday were also predicted to have increased, and nearly equal counts, but that were only 60–66 % of the Saturday high. Visitation decreased on earlier weekdays reaching a minimum on Mondays. Many researchers recognize the need to compartmentalize business days (Monday through Friday) from non-business days (Saturday and Sunday) in studies of recreational fishing given the obvious bias towards weekends for recreation (Parnell et al., 2010; van Poorten et al., 2015; Keller et al., 2016; Flynn et al., 2018). In multiple ecosystem settings including coastal Tasmania (Flynn et al., 2018), remote Canadian lakes (Askey et al., 2018), and coastal Vancouver Island (Lancaster et al., 2017), recreational angler effort on weekend days was 2−3 times higher than weekday effort. This value is consistent with that reported here where visitation was predicted to be 3–5 times higher on Saturday and ~2−3 times higher on Friday and Sunday, than Monday through Thursday. Given the diversity of ecosystems and similarity of these patterns, this difference may be typical for many recreational fisheries and could be used as a general value in less known systems until location-specific estimates of weekday versus weekend visitation can be determined. Such a simplifying assumption must be used cautiously however, especially in locations known to attract visitors that may be on vacation during weekdays. In contrast to other studies, we observed a clear peak on Saturday that was distinct from visitation levels on Sunday, which were 33 % lower. This could be due to the attendance of

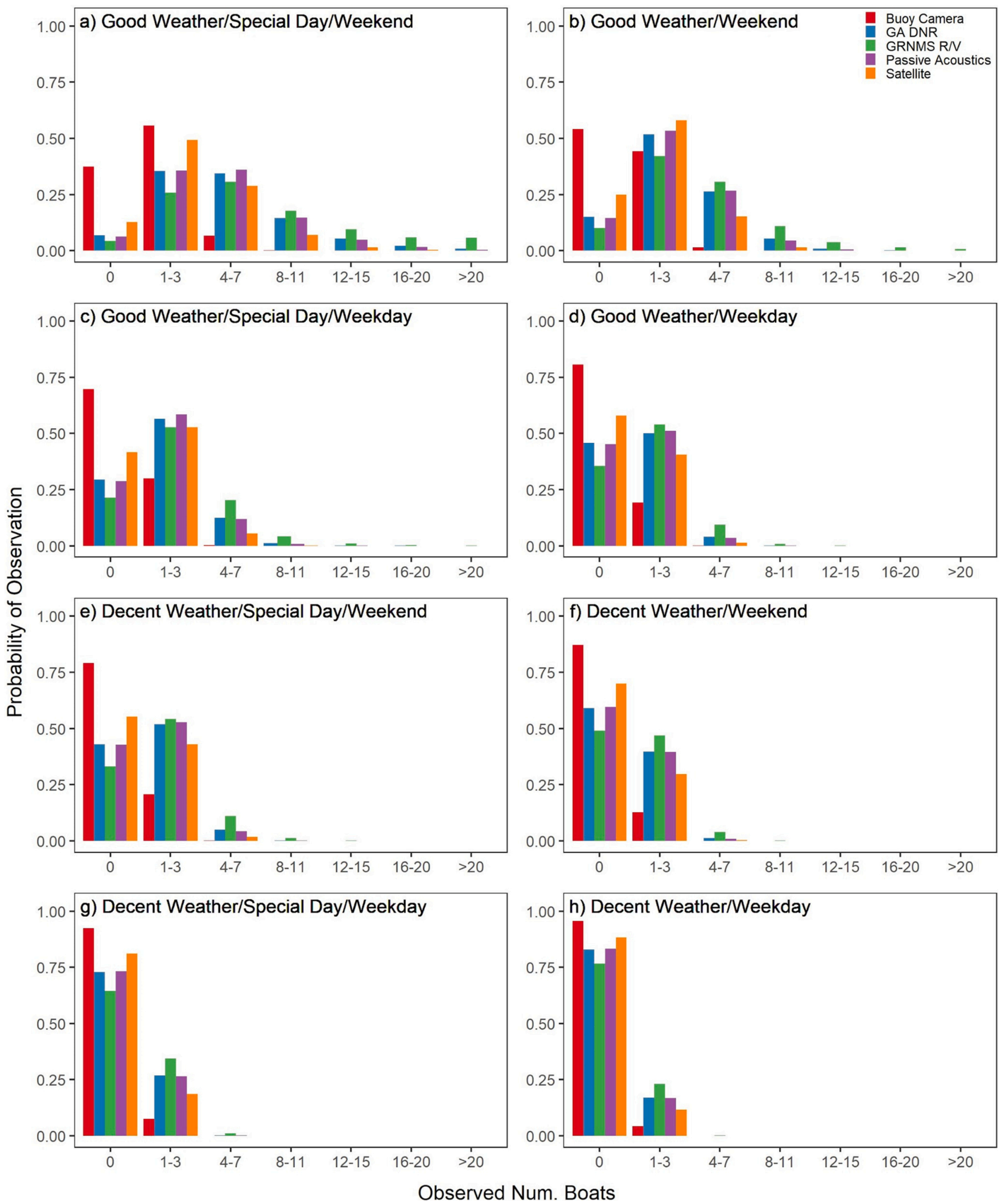

Fig. 6. Probability of observing different numbers of boats across weather/calendar scenarios.

Sunday religious services, the study area being located off Georgia, which is in the top ten of US states in terms of church attendance (Newport, 2015). Also somewhat different from other studies (Lancaster et al., 2017; Askey et al., 2018), was that Friday was equally as high as Sunday visitation suggesting perhaps that anglers at Gray's Reef are more likely to get an early start on weekend recreation.

In some cases, business day status does not influence fishing such as in the recreational squid fishery in parts of the Mediterranean Sea (Cabanellas-Reboredo et al., 2014). The short, 2−3 hour duration of excursions, and evening departure times of the nighttime squid fishery, are amenable to trips on any day of the week. Other locations that are farther offshore and visited during the daytime such as GRNMS (Kendall et al., 2020), would require a larger amount of time just for transit to and from the site, and may be incompatible with brief weekday excursions.

It is important to note that variables that were not selected in the model may not be "unimportant" in the sense that anglers do not consider them when planning an offshore excursion, they just did not meet our definition of statistical importance (i.e., were dropped prior to the modeling stage or were not in the model with lowest AICc). Variables may be excluded because they are poorly related to the observed boat counts. For example, many anglers associate barometer trends with suspected fish movement and behaviors (Poveromo, 2012). They incorporate that knowledge into decisions on when and how to fish. Even though some anglers use such information while planning offshore fishing excursions, the direction of daily barometric pressure change as measured from the data buoy was simply not a useful predictor of

Table 2
Comparison of models fit with different sets of boat count data. CV represents the coefficient of variation of the predicted mean count for a good weather Saturday (not special). Check marks indicate predictor variables that were in the best model.

Model	Deviance Explained (%)	N obs	CV	Count Method	Day of Week	Special Day	Forecasted Max Seas	Forecasted Max Winds	Forecasted showers	Forecasted storms	Small craft advisory	Air Temp	Water temp	Wave height	Wind speed
All data	43.4	593	0.15–0.45	✓	✓	✓							✓	✓	
Only Buoy Camera	50.6	187	0.93		✓	✓		✓	✓				✓		
Only GA DNR and GRNMS R/V	23.7	24	0.27				✓					✓			
Only Passive acoustics	38.8	353	0.17		✓	✓							✓	✓	
Only Satellite	79.8	29	0.27		✓									✓	

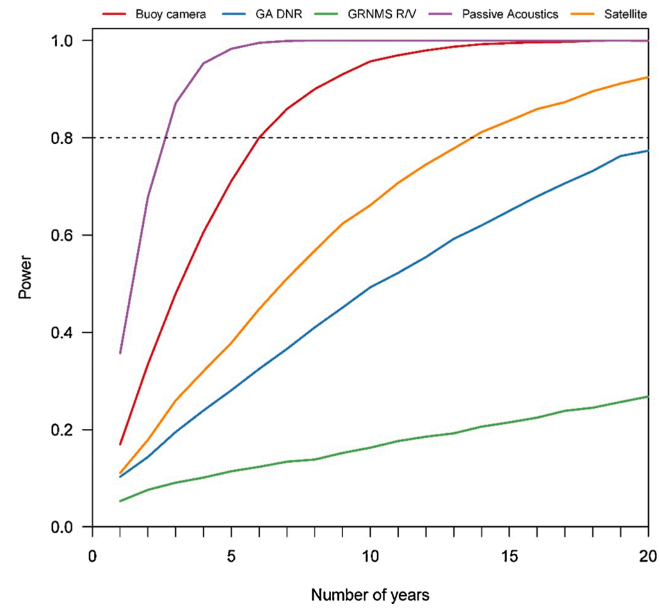

Fig. 7. Statistical power to detect (alpha = 0.05) a 25 % increase in visitation as a function of the number of years of typical count data for each boat-count method. The dotted line denotes a power of 80 % probability of detecting the increase.

visitation. In another example, boaters avoid thunderstorms, but the influence of that variable was not in the top performing model.

Other variables were excluded because they were highly correlated with another predictor that better explained the boat counts in the models. Highly correlated variables essentially represent the same information in the models and are therefore redundant. For example, the intuitively important variable of wind speed was correlated with wave height. Because wave height better explained the number of boats, wind speed was not defined as an important predictor in the modeling framework. If wave height had not been available in the modeling process, wind speed would likely have taken its place. Similarly, small craft advisories almost certainly discourage many from venturing offshore, but were not identified as an important predictor. This was likely due to a stronger relationship between boat counts and a different predictor, in this case, wave height.

It is also recognized that a diversity of additional influences may affect visitation although it was not possible to include them all here. Several other calendar-based predictors were initially considered but eliminated. For example, demographics of offshore anglers in coastal Georgia often include interest in other outdoor activities such as fishing for inshore species and hunting. However, dates for those seasons were either too few (e.g., opening day surge in hunting) to have adequate sample size, too diffuse (e.g., protracted fishing seasons) to have a measurable effect, or their effects were simply too uncertain to incorporate into the models.

4.2. *Predicted boat counts and the importance of count method*

The method of counting boats was also identified as an important predictor. A detailed breakdown of each technique's acquisition and logistical pros and cons is provided in Kendall et al. (2020) and has been addressed for various observation techniques by others (Fraidenberg and Bargmann, 1982; McCluskey and Lewison, 2008; Bruno et al., 2011; Holdsworth et al., 2018; Hartill et al., 2020). Here, we focus on their informative and predictive properties. Bad weather likely affects the efficacy of some boat count techniques more than others, however, because the pattern of decline in counts is consistent among techniques as the weather deteriorates, this was not suspected to be a major source of bias in the results. Techniques reliant upon observers in boats on the water had among the highest daily counts but also the lowest sample sizes and are biased toward times when boating is safe. The model fit to these data alone failed to detect the influence of calendar-based variables on visitation, probably due to their low sample size on weekdays (GADNR) and weekends (GRNMS R/V), whereas the other count methods identified the influence of both environmental and calendar-based variables. The statistical power of on-water boat count methods was relatively low because their annual sample sizes were low, especially GRNMS R/V. In our example power analysis for GA DNR, more than 20 years with 18 on-water boat counts per year would be needed before and after an increase of 25 % in visitor use to have 80 % statistical power to detect that change. Many more years would be required by GRNMS R/V counts. Without a dramatic increase in annual effort and investment in these techniques, they would be unlikely to detect change in useful timeframes on their own.

In contrast, passive acoustic monitoring provided an automated data stream, the highest number of observed counts, and broadest coverage with respect to environmental conditions and calendar dates throughout almost the entire year. The higher number of samples resulted in the highest statistical power such that only 3 years of data would be needed before and after an increase of 25 % in visitor use to have 80 % statistical power to detect that change. However, the passive acoustic counts were spatially biased as a result of the narrow and variable detection range surrounding it (~1 to 4 km depending on ambient noise). Similar to the acoustics, the buoy camera can potentially provide continuous monitoring throughout the year. However, the buoy camera had the lowest actual counts, possibly due to its low resolution and limited effective distance (~2 km depending on visibility) around the data buoy. This resulted in lower statistical power such that 6 years of data would be needed before and after an increase of 25 % in visitor use to have 80 % statistical power to detect that change.

Based on satellite counts, 14 years of data would be needed before and after an increase of 25 % in visitor use to have 80 % statistical power to detect that change. It is important to note that all these estimates of statistical power were calculated under several simplifying assumptions. For example, the simulated data assumed the same environmental conditions every year; those of 2019. Also, a simple model was used to test for a change, whereas a more complex model that accounted for the effects of predictors could provide different statistical power. Nevertheless, the example demonstrated here likely provided reasonable estimates of the relative differences among count methods and the number of years of data that would be needed from each of them. This is an important consideration in studies seeking to identify which counting techniques provide the needed information on timescales relevant to management. For example, MPA and fishery management plans are often revised on a 5−10 year cycle (NOAA, 2014; Levin et al., 2018). Adaptive management requires that robust information be collected over similar intervals.

Although our study indicates that weekend days with favorable environmental conditions have the highest expected counts of boats, it is also useful to know how many boats might be encountered on other days of the year to develop a more complete understanding of the patterns of visitation. The weather and calendar day scenarios presented here can be used to set expectations for how many boats may be seen with each technique. The scenarios can be easily referenced by data collectors to determine the probabilities of counting different numbers of boats under particular dates and conditions to achieve a target number of boat encounters (e.g., law enforcement). Regardless of the method used, the actual number of boats counted on a given day can vary substantially, even on the same day of the week under the same environmental conditions. Furthermore, it is also useful to recognize that there is usually a considerable probability of not counting any boats, especially on weekdays when weather conditions are sub-optimal.

Unfortunately, none of the boat count methods evaluated here provided unbiased estimates of the actual number of boats that visited GRNMS. The estimated annual number of boats based on daily conditions and calendar variables in 2019 varied from 64 (buoy camera) to 374 (GRNMS R/V). Some methods provided better temporal coverage within a day whereas other methods provided better spatial coverage of the area. For example, the passive acoustics continuously recorded boat noise which provided good temporal monitoring, but these counts only covered a portion of GRNMS. Other techniques provide more comprehensive spatial coverage but suffer from limited temporal coverage. For example, the satellite images used here could view the entire area, but only provided a snapshot of activity at one time of day every few days. It may be possible to leverage the empirical relationships among coincident observations from multiple boat count datasets to extrapolate to a more complete temporal and spatial sampling frame (Bruno et al., 2011; van Poorten et al., 2015; Keller et al., 2016; Holdsworth et al., 2018). For example, establishing the relationship between the acoustic counts (continuous but limited spatial coverage) and satellite counts (entire sanctuary but snapshot in time) may enable reciprocal use of the strengths of one dataset to account for the biases of another.

Despite the differences among the boat count datasets, there was consistency in the variables identified to have an influence on them. Most counting techniques identified at least one environmental and calendar based variable. Having data from multiple independent count methods provides more confidence in conclusions about important predictor variables (Parnell et al., 2010; Sunger et al., 2012; Hartill et al., 2016; Holdsworth et al., 2018; Lynch et al., 2020). Furthermore, multiple boat count datasets used in concert were more useful than any one individual dataset on its own due to larger sample size and greater statistical power.

5. Conclusion

The approach presented here for understanding recreational visitation of offshore or remote areas can be adopted elsewhere. The process involved using multiple boat count datasets, identifying an initial set of predictor variables, reducing that set through preliminary analysis and model selection, fitting a model to the boat count datasets as a function of the predictor variables, identifying a small set of realistic scenarios during which boat counts could be conducted, and using the fitted model to determine the number of samples that each technique would require to detect a specific amount of change in visitation.

Predictors representing the general categories of weather conditions, season, day of the week, and special date status are all important types of information to consider for offshore visitation that have been identified in this and other studies (Fraidenberg and Bargmann, 1982; Parnell et al., 2010; Cabanellas-Reboredo et al., 2014; Keller et al., 2016; Lancaster et al., 2017; Lynch et al., 2020). Different boat count datasets will relate best to specific predictors that represent these broad general categories of information (air and water temperature represent season, wave height and wind speed represent boating safety and comfort).

The estimated counts of boats visiting GRNMS on a given day varied widely depending on the count method, primarily because of differences in the temporal and spatial extent of sampling for each method. Count methods also varied greatly in terms of sample size with some methods providing many more daily counts covering a wider range of conditions and dates than others. Methods that provided fewer daily counts from a limited range of conditions and dates were less informative about the variables influencing visitation. Also, methods with smaller sample sizes or fewer observations of boats had less statistical power to detect changes in visitation. A full assessment of the usefulness of different count methods must also consider the cost of data collection (e.g., Sunger et al., 2012), a topic beyond our scope. The most valuable methods would be those that collect more data for less cost. Combining the scenarios and power analysis explored here with other forms of social science data such as questionnaires or creel surveys, can be used to develop economic impact models, fisheries mortality estimates, spatial management tools (e.g., MPAs), and other forms of actionable information on the effects of visitor use (Parnell et al., 2010; Hartill et al., 2016; Bova et al., 2018; Burns et al., 2020).

Author contributions

M. Kendall was the principle investigator on the study, wrote and edited the manuscript and guided the analysis. B. Williams and A. Winship wrote and edited the manuscript and guided and conducted the analysis. M. Carson, K. Grissom, T. Rowell, J. Stanley, and K. Roberson collected and processed input data, interpreted results, and edited the manuscript.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships tha

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Appendix A. List of all predictor variables that were initially compiled. Many were eliminated prior to model fitting by examining correlations among variables, and eliminating one from pairs of closely related predictors (e.g. wind speed at 5:50 AM vs 10:50 AM). Variables were considered correlated if Pearson's r was ≥ 0.6. Check marks in the modelled column denote variables that went into the model fitting process but do not necessarily mean that the predictor was used in the best model

Predictor	Source	Modelled	Correlated with:
Forecasted maximum wave height (AM)	Weather Service Forecasts	✓	Measured wave height (5:50 AM & 10:50 AM), measured wind speed (5:50 AM & 10:50 AM), small craft advisory (AM & PM), forecasted max wind speed (AM & PM), forecasted max wave height (PM)
Forecasted maximum wind speed (AM)	Weather Service Forecasts	✓	Measured wave height (5:50 AM & 10:50 AM), measured wind speed (5:50 AM & 10:50 AM), small craft advisory (AM & PM), forecasted max wind speed (PM), forecasted max wave height (AM & PM)
Forecasted small craft advisories (AM)	Weather Service Forecasts	✓	Forecasted max wave height (AM & PM), forecasted max wind speed (AM & PM), forecasted small craft advisory (PM), measured wave height (5:50 AM & 10:50 AM)
Forecasted showers (AM)	Weather Service Forecasts	✓	Forecasted showers (PM), forecasted thunderstorms (AM & PM)
Forecasted rain (AM)	Weather Service Forecasts		none
Forecasted thunderstorms (AM)	Weather Service Forecasts	✓	Forecasted thunderstorms (PM), forecasted showers (AM & PM)
Forecasted maximum wave height (PM)	Weather Service Forecasts		Measured wave height (5:50 AM & 10:50 AM), measured wind speed (5:50 AM & 10:50 AM), small craft advisory (AM & PM), forecasted max wind speed (AM & PM), forecasted max wave height (AM)
Forecasted maximum wind speed (PM)	Weather Service Forecasts		Measured wave height (5:50 AM & 10:50 AM), measured wind speed (5:50 AM & 10:50 AM), small craft advisory (AM & PM), forecasted max wind speed (AM), forecasted max wave height (AM & PM)
Forecasted small craft advisories (PM)	Weather Service Forecasts		Forecasted max wave height (AM & PM), forecasted max wind speed (AM & PM), forecasted small craft advisory (AM), measured wave height (5:50 AM & 10:50 AM)
Forecasted showers (PM)	Weather Service Forecasts		Forecasted showers (AM), forecasted thunderstorms (AM & PM)
Forecasted rain (PM)	Weather Service Forecasts		none
Forecasted thunderstorms (PM)	Weather Service Forecasts		Forecasted thunderstorms (PM), forecasted showers (AM & PM)
Measured wind speed (5:50 AM)	National Data Buoy Center		Measured wave height (5:50 AM & 10:50 AM), measured wind speed (10:50 AM), forecasted max wind speed (AM & PM), forecasted max wave height (AM & PM)
Measured wave height (5:50 AM)	National Data Buoy Center		Measured wave height (10:50 AM), measured wind speed (5:50 AM & 10:50 AM), small craft advisory (AM & PM), forecasted max wind speed (AM & PM), forecasted max wave height (AM & PM)
Measured water temperature (5:50 AM)	National Data Buoy Center		Measured air temperature (5:50 AM & 10:50 AM), measured water temperature (10:50 AM)
Measured dominant wave period (5:50 AM)	National Data Buoy Center		Measured wave period (10:50 AM)
Measured pressure change (5:50 AM)	National Data Buoy Center		none
Measured air temperature (5:50 AM)	National Data Buoy Center		Measured water temperature (5:50 AM & 10:50 AM), measured air temperature (10:50 AM)
Measured wind speed (10:50 AM)	National Data Buoy Center	✓	Measured wave height (5:50 AM & 10:50 AM), measured wind speed (5:50 AM), forecasted max wind speed (AM & PM), forecasted max wave height (AM & PM)
Measured wave height (10:50 AM)	National Data Buoy Center	✓	Measured wave height (5:50 AM), measured wind speed (5:50 AM & 10:50 AM), small craft advisory (AM & PM), forecasted max wind speed (AM & PM), forecasted max wave height (AM & PM)
Measured water temperature (10:50 AM)	National Data Buoy Center	✓	Measured air temperature (5:50 AM & 10:50 AM), measured water temperature (5:50 AM)
Measured dominant wave period (10:50 AM)	National Data Buoy Center		Measured wave period (5:50 AM)
Measured pressure change (10:50 AM)	National Data Buoy Center		none
		✓	Measured water temperature (5:50 AM & 10:50 AM), measured air temperature (5:50 AM)

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(*continued*)

Predictor	Source	Modelled	Correlated with:
Measured air temperature (10:50 AM)	National Data Buoy Center		
Special dates (holidays, tournaments, fishing seasons)	Calendar	✓	none
Day of the week	Calendar	✓	none
Count method		✓	none

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